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Operational Productivity, Corporate Social Performance, Financial Performance, and Risk in Manufacturing Firms

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We examine the relationship between Operational Productivity (OP), Corporate Social Performance (CSP), Financial Performance (FP), and risk. Our sample frame comprises 476 firms in nine US manufacturing industries during the period 1999–2009. We employ DEA-based measures for OP and CSP, two operationalizations for FP to reflect current profitability and market value, and two operationalizations for risk to reflect bankruptcy risk and stock price volatility. We confirm that OP is essential for good financial performance and reduced risk (as expected), but the main effects of CSP are mixed. Importantly, we find that OP moderates the CSP–FP and CSP–risk relationships. Specifically, if OP is poor, CSP is of limited benefit to FP or risk. However, at or above a threshold level of OP, firms can use CSP to build upon it to yield further improvements in FP and reductions in risk. We discuss the implications of our findings for theory and practice.

Key words: productivity; corporate social performance; operations strategy; financial performance; financial risk
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1. Introduction

Although manufacturers have long understood the importance of productivity to their economic success, and there is an extensive literature examining the economic impacts of corporate social performance, few researchers have jointly considered the relationships between productivity, corporate social performance, and economic performance. These relationships are of particular interest to the operations management (OM) discipline because of its historic focus on productivity, and its increasing concern with corporate social performance (Kleindorfer et al. 2005). With its *raison d'être* to efficiently and effectively manage processes that transform inputs into outputs, OM is fundamentally concerned with operational productivity, a measure of outputs per input. A more recent but growing concern for OM is corporate social performance and sustainability. Kleindorfer et al. (2005) note several factors that are driving this growth: (i) scarcity and cost of materials and energy; (ii) public pressure for social and environmental performance; (iii) awareness of triple bottom line issues; and (iv) strong NGO activity.

To adequately judge economic performance, we must consider both return and risk since improvements in financial performance (return) might be offset by increased variability (risk). For example, increased operational productivity might improve current profitability but could also expose the firm to risks if resources such as workers, machines, or factories are overutilized. Similarly, corporate social performance might contribute to revenues and returns by improving the firm's public reputation, but could also increase financial risks if those investments are too costly. Consideration of both risk and return thus provides a more complete picture of the overall economic performance of the firm.

The foundational nature of the relationship between operational productivity and economic performance for manufacturing firms suggests that the impact of corporate social performance (hereafter referred to as CSP) on returns and risks should consider the role of productivity in those relationships. In other words, when productivity is low, the manufacturer is fighting for economic survival and even superior CSP might not help. However, when productivity is high, CSP might have the ability to further improve economic performance. Specifically, we consider whether operational productivity (hereafter referred to as OP) moderates the effects of CSP on financial performance (hereafter referred to as FP) and risk. We do so by estimating the OP·CSP interaction effects on FP and risk, and we also determine whether manufacturers that excel in both OP and CSP benefit from FP

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(risk) that is greater than (less than) that of firms that excel in only one of these dimensions.

Before proceeding, it is important to define our use of CSP and operational productivity. CSP has a variety of definitions but they share a common focus on the firm's impacts to the public or society beyond its direct technical or economic interests (Carroll 1999, Dahlsrud 2008). For example, Turban and Greening (1997) define CSP as the firm's responsibilities to stakeholder groups such as employees and the community, in addition to its traditional responsibilities to shareholders. Chen and Delmas (2011) note that CSP practices comprise multiple dimensions including community relations, environmental programs, and human rights, among others. In this study, we adopt the definition of Pinney (2001) who defines CSP as a set of management practices that minimize negative impacts and maximize positive impacts of firm operations on society. Also consisting of multiple dimensions, operational productivity is larger in scope than just labor productivity (Chew 1988). Given our focus on manufacturing operations, we define operational productivity to include the varied manufacturing inputs—including labor, facilities, equipment, and inventory—that operations managers control to maximize firm outputs.

To examine our research questions, we collect data for US firms in nine different manufacturing industries during the period 1999–2009. We use DEA to operationalize OP and CSP at the firm-level, permitting us to consider multiple inputs and outputs for each measure. OP is computed using variable returns-to-scale (VRS) DEA with Compustat data. Employing the work of Chen and Delmas (2011), our CSP measure is obtained using an ordinal DEA methodology with data from Kinder, Lydenberg, and Domini, Inc. (KLD) Research and Analytics as inputs and outputs for various dimensions of CSP. We operationalize FP and risk using two measures for each, an accounting-based measure and a market-based measure. We use Compustat and CRSP data to compute our FP measures capturing impacts to current profitability (accounting-based), and market value (market-based). Our two measures for risk are bankruptcy risk (accounting-based) and stock price volatility (market-based). To analyze the relationships between OP, CSP, FP, and risk, we begin by examining the basic relationships between the variables, followed by a panel data estimation approach.

With the model, measures, and methodology that we employ, we contribute to the extant literature by taking a uniquely OM perspective that investigates the role of OP in the CSP–FP and CSP–risk relationships. As recapped by Margolis and Walsh (2001), Orlitzky et al. (2003), and Surroca et al. (2010), many studies employ contextual variables to examine the financial impacts of CSP but the studies are generally from marketing, strategy, or ethics perspectives. For example, variables considered include consumer moral values (Schuler and Cording 2006), stakeholder management strategy (Mattingly and Berman 2006), institutional logics (Orlitzky 2011), and media publicity (Zyglidopoulos et al. 2012), among others. Despite anecdotal references to the relationship between OP, CSP, and financial performance (Kleindorfer et al. 2005, Porter and van der Linde 1995), few studies explicitly consider the role of productivity. Further, studies in the CSP-risk domain do not consider the role of productivity. While some focus on the risk performance of a portfolio of stocks (e.g., Lee and Faff 2009, Boutin-Dufresne and Savaria 2004), other studies at the firm-level present findings on how individual dimensions of CSP differentially influence risks (Bouslah et al. 2013).

A related research stream is the "lean and green" literature (e.g., King and Lenox 2001, Pil and Rothenberg 2003, Rothenberg et al. 2001) that jointly considers lean and environmental capabilities, and suggests that they are complementary. We draw arguments from the lean and green literature, but we extend it in a number of important ways. Although both lean researchers (e.g, Hofer et al. 2012) and green researchers (e.g., Klassen and McLaughlin 1996) have examined the FP impacts of those capabilities independently, the joint economic effects of lean and green have not been examined. Further, as a management philosophy, lean focuses on value maximization within processes and is a construct that can involve several entities including customers, within-firm operations, and suppliers (Shah and Ward 2007). In our research context, we make no presumption of a particular philosophy, and instead focus on the less restrictive construct of OP that is achievable by a variety of means such as a focus on efficiency, or trading labor for equipment. Also, CSP is a broader construct than environmental performance as it addresses multiple areas other than environment including community relations, human rights, etc. Thus, we extend the lean and green literature to encompass the more general constructs of OP (rather than lean) and CSP (rather than green), and to consider not only their impacts to FP but also impacts to risk.

Next, our work is one of the first applications of the CSP measure developed by Chen and Delmas (2011). Multiple studies note that the divergent nature of CSP dimensions and measures often lead to problems with measurement and analyses in research (Wood 2010, Delmas and Blass 2010, Orlitzky 2013). In response, Chen and Delmas (2011) propose an aggregation method for CSP based on DEA that improves upon the deficiencies of other aggregate measures. The resultant measure provides a single number that compares the relative CSP implementations of different firms, and accounts for both their strengths and weaknesses in multiple dimensions of CSP. The measure of Chen and Delmas (2011) recognizes that firms might choose to excel in one or more aspects of CSP (e.g., environment, employee relations) as compared to others (e.g., human rights, community relations) dependent on their particular business model and industry. By comparing the firm's performance in multiple CSP areas against a set of peer firms, DEA calculates a set of optimal weights that maximize the firm's score, permitting multiple paths for firms to achieve high levels of CSP.

Finally, we utilize two measures of financial performance and two measures of financial risk to account for the differing elements of both financial returns and risk. Surprisingly, few studies of the economic impact of CSP incorporate measures for both returns and risks. Focusing on financial returns, we employ ROA as a measure of current profitability that is commonly used to assess the relationship between both CSP and OP on FP. Our second measure of FP is Tobin's *q*. Studies note that Tobin's *q* is a good reflection of the firm's intangible assets, including its intellectual capital in terms of technology and market strength (Megna and Klock 1993). Thus, Tobin's *q* provides a market-facing measure, unlike ROA, an accounting-based measure that focuses on current profitability. It is likely that CSP might provide firms intangible benefits that they can leverage to increase their market value. Focusing on financial risk, our first measure of risk, Altman *Z*, is a gage of the firm's bankruptcy risk (Altman 1973). Altman *Z* is a relatively unique measure in the OM literature but is commonly employed in the finance literature. As a measure of bankruptcy risk, Altman *Z* permits us to examine the ability of firms to maintain financial viability while pursuing social responsibility initiatives. Given that Altman *Z* is primarily an accounting-based measure, we also employ a purely market-facing measure of risk, stock price volatility.

To foreshadow our results, we find from our analyses that many manufacturing firms excel in both OP and CSP but there is considerable variation in performance on both measures. Examination of the data suggests that OP is strongly and positively associated with ROA. The strength of this relationship is not surprising to operations managers and theorists. However, OP has a weaker relationship with Altman *Z* and Tobin's *q*, and OP is not significantly associated with reduction in stock price volatility. For the firms in our study, the most beneficial values of ROA, Tobin's *q*, and stock price volatility are all associated with superior performance in both OP and CSP rather than superior performance in only one dimension. This relationship, however, does not necessarily hold for Altman *Z*. Most importantly, we find that the economic effects of OP and CSP are not independent but that instead OP moderates the CSP–FP and CSP–risk relationships. Our finding suggests that OP forms a foundational capability on which managers can build CSP in order to realize superior economic performance. Specifically, the financial impact of CSP can only be realized with a threshold level of OP. Without sufficient OP, CSP has little significant economic impact. Our results indicate that although OP is critical to economic performance, managers should not focus solely on either OP or CSP. Rather, cultivating both OP and CSP is associated with the greatest financial performance and the least risk.

2. Theory and Literature Review

We review the literature to consider the theoretical and empirical research on the relationships between OP, CSP, FP, and risk. We first recap the literature on the independent effects of OP on FP and risk in section 2.1, and of CSP on FP and risk in section 2.2. In section 2.3, we provide theoretical support and motivation for the joint effects of OP and CSP on FP and risk.

2.1. Operational Productivity, Financial Performance, and Risk

Although the link between OP, FP, and risk is intuitive and well-known for manufacturing firms, we consider it for two reasons. First, given our interest in the moderating effects of OP on the CSP–FP and CSP-risk links, we must also consider the direct effect of OP on FP and risk. Second, we use the OP-FP and OP–risk relationships as baselines to compare the relative strength of the CSP–FP and CSP–risk relationships.

By definition, productivity is a ratio of outputs to inputs. Productive firms are efficient, achieving greater outputs per input. Improvements in firm productivity can be accomplished by a variety of means. For example, the firm's focus might be on increasing outputs such as sales by introducing new, successful products while other inputs are held constant. Such a strategy is likely dependent on firm capabilities in marketing and product development. Conversely, the firm's productivity focus might be on the most efficient use of inputs assuming constant outputs. As explained by Hayes and Wheelwright (1984), productivity in manufacturing firms tends to focus on the input side, and is increased both by using existing assets more efficiently, and by the ability to substitute operational resources for one another, such as equipment for labor or inventory for capacity. Although input efficiency, as measured by productivity, is not a

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guarantee of financial success, it can be an essential component of financial performance, particularly for manufacturing firms. Baily et al. (1995) discuss the important relationship between the achievement of world class productivity levels and competitive success in manufacturing.

Evidence of the OP-FP link is provided by researchers that examine the relative financial performance effects of firm capabilities in operations, marketing, R&D, and other dimensions. Dutta et al. (1999) define operations capability as the ability to increase output volumes while minimizing the inputs of labor and capital, a construct very similar to OP. They demonstrate that operations capability has a significant positive effect on financial performance. Another definition of operations capability similar to OP is provided by Krasnikov and Jayachandran (2008, p. 2) as "…performing organizational activities efficiently and flexibly with a minimum wastage of resources." In their meta-analysis of 261 studies, Krasnikov and Jayachandran (2008) find a strong, positive association between operations capability and firm performance.

Greater OP can reduce risk in a number of ways. Given that greater OP results in greater FP, firm viability is improved and the risk of bankruptcy is lessened. Firms with greater FP are also less likely to be leveraged, and hence exposed to less risk. As İmrohoroğlu and Tüzel (2014) discuss, low productivity firms are more vulnerable to business cycles and hence riskier than high productivity firms. Firms that can achieve greater sales via less use of employees, assets, inventory, or other operational inputs (i.e., firms with high OP) are exposed to less risk than firms with similar sales but greater use of inputs since each input can introduce risk. İmrohoroğlu and Tüzel (2014) demonstrate that firm-level productivity is positively correlated with investments and financial performance, and negatively correlated with financial risk. Accordingly, we expect that for manufacturing firms, OP is strongly and positively associated with financial performance, and negatively associated with risk.

2.2. Corporate Social Performance, Financial Performance, and Risk

The literature examines several mechanisms for the association between improved CSP, improved FP, and reduced risk. Arguments and empirical evidence have been presented for both directions of causality. For example, Waddock and Graves (1997) argue and demonstrate that CSP and economic performance are mutually reinforcing, forming a "virtuous circle." Although many researchers seek to prove the direction of causality, it is not our aim in this project. Rather, our research aim is to consider whether OP moderates the relationships between CSP and economic performance, and to establish whether the most successful manufacturing firms excel only in OP or in both CSP and OP.

The drivers of the CSP–FP relationship include both cost and revenue impacts. We begin by considering the potential cost reduction aspects of two CSP dimensions, employee relations and environmental performance. Superior employee relations can decrease absenteeism and turnover and their attendant costs (Datta et al. 2005, Hansen et al. 2011). Environmental performance can reduce the cost to develop and maintain policies and procedures (Dowell et al. 2000), the consumption of various production inputs including energy and materials (Rothenberg et al. 2001, Sroufe 2003), and the amount of waste (Porter and van der Linde 1995). Environmental performance can also cut inbound and outbound logistics costs from reduced product weights and packaging (Rao and Holt 2005). Pollution prevention can lower disposal and mitigation costs, and might also avoid the cost of installing and operating expensive pollution control devices (Hart and Ahuja 1996). Of course, the slack resources available in financially successful firms can also enable CSP. Firms with slack resources can better afford the investments and/or employment practices needed to improve CSP.

Corporate Social Performance can also increase firm revenues by enhancing reputation. Improved recognition and reputation potentially lead to increased sales and/or favorable investor reaction. Further, firms with superior reputation are likely more profitable (Herremans et al. 1993). For example, public recognition is a significant motivator for firms to voluntarily join the EPA Industrial Toxics Project aimed at reducing hazardous chemical emissions (Khanna and Damon 1999).

From a risk perspective, superior employment practices reduce risks of workplace lawsuits (Rousseau 1989) and health and safety issues (Danna and Griffin 1999). Good environmental performance reduces or eliminates emissions, enabling firms to reduce the likelihood of environmental crises such as spills, leaks, or contamination (Reinhardt 1999). In addition, the CSP dimension of effective community relations can reduce firm risk of tax increases or added regulation (Waddock and Graves 1997). Godfrey (2005) and Godfrey et al. (2009) describe CSP as insurance for the firm. Specifically, they demonstrate that CSP can mitigate risk by building moral capital and helping firms protect themselves from financial losses due to negative events. However, if CSP efforts are costly and/or not well targeted or well communicated, they might increase financial risk. As Weber (2008) explains, firms with high-profile CSP efforts can sometimes increase their risk of being targeted by NGOs and activists.

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Beyond economic arguments, stakeholder theory is a commonly used approach to explain the positive relationship between CSP and economic performance. As argued by Jones (1995), CSP is a manifestation of management's ability to develop and maintain trusting relationships with multiple stakeholders. He proposes that such relationships improve economic performance beyond the expectation of economic theory by leveraging trust and cooperation to ease transactions. Since effective stakeholder engagement enables fundamental business objectives as attracting quality employees, and avoiding fines and litigation, Waddock and Graves (1997) suggest that CSP is not discretionary but instead directly linked to the quality of management. Consequently, they label this as good management theory, and argue that, with good management, CSP improves FP.

Despite the above arguments, the CSP literature reports mixed impacts of CSP on FP and risk. To investigate the mixed findings in the CSP–FP relationship, Orlitzky et al. (2003) conduct a meta-analysis of 52 studies; they conclude that, despite significant variation, the CSP–FP relationship is generally positive. Similarly, Orlitzky and Benjamin (2001) meta-analyze 18 studies of the CSP–risk relationship, and conclude that the relationship is generally negative.

2.3. Joint Effects of Operational Productivity and Corporate Social Performance

Thus far, we have discussed the independent impacts of CSP and OP on financial performance and risk. We now provide arguments for their joint influence. From a theoretical perspective, there are at least three arguments for nonlinear, or moderating, effects of OP on the CSP–FP and CSP–risk relationships. Firms with good performance in OP are more likely to have valuable resources such as: (i) good management that can extract economic benefits from CSP; (ii) capabilities required to effectively leverage CSP inputs; and (iii) slack that can be used to offset the sometimes costly or time-intensive inputs required for CSP without harming FP or increasing risk. Conversely, firms with poor performance in OP are less likely to possess these resources that enhance the CSP–FP and CSP–risk relationships. Thus, we expect when OP is low, CSP will have little or no benefit to FP or risk but when OP is high, CSP is associated with superior FP and reduced risk. In the following paragraphs, we address the value, rarity, inimitability, and non-substitutability, the VRIN characteristics of the Resource Based View outlined by Barney (1991), of these three resources.

Koprowski (1981) argues that productivity achievement is a necessary objective of good managers. Van Reenan (2011) reviews the logic and theory that management quality is a primary driver of productivity. Thus, it seems reasonable that good management is a likely prerequisite to superior productivity (high OP). From a VRIN perspective, management quality is considered a resource as it adds value by improving firm efficiencies needed to achieve high OP. Further, as a socially complex form of human capital, good management is difficult to imitate. Consistent with the arguments of good management theory (Waddock and Graves 1997), Alexander and Buchholz (1978) argue that managers cannot be socially aware and concerned unless they possess the requisite skills to run a superior company in the traditional sense of managing productivity to achieve financial performance. From an operations perspective, Deming (1981) argues that productivity improvement requires consistent management action to work on appropriate processes required to achieve the necessary levels. The answer to superior productivity thus likely resides in superior management (Deming 1981). Further, the prioritization of achieving sufficient OP is consistent with researchers such as Friedman (1970) and Carroll (1979) who argue that the fundamental priority of business is commercial. As Carroll (1979, p. 500) states: "The first and foremost social responsibility of business is economic in nature." Thus, it is likely that good management is a key resource that underpins superior productivity. Such a key resource is also likely to benefit firms in leveraging CSP for superior financial performance. Following the same rationale, it is likely that firms with superior OP are successful in more effectively leveraging CSP for reduction of financial risk. Hendry (2006) suggests that managers in firms with superior CSP might be better at assessing the key needs of different stakeholders and meeting their needs. While meeting these needs can help the firms in reducing risks, it is likely that firms with superior management can more effectively mitigate the risks and minimize the negative impact on firms.

In addition to good management, other firm resources required to achieve greater OP include organizational capabilities in waste reduction, employee involvement, and continuous improvement. Russo and Fouts (1997) argue that such capabilities are causally ambiguous, and difficult to imitate. These capabilities are focused on the cost efficiency of inputs, a factor that has also become increasingly important for CSP. Researchers note that the lack of financial gains sometimes associated with CSP might be due to the increased costs incurred (e.g., McWilliams and Siegel 2001, Barnett and Salomon 2012). Kleindorfer et al. (2005, p. 484) note that: "The question for companies has become not whether to commit to a strong environmental, health, and safety record, but how to do so in the most cost-effective manner." Lean and green researchers note

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that capabilities such as those associated with greater OP can enable firms to reduce the costs of environmental efforts, and thus achieve greater financial benefits from them (e.g., Florida 1996, King and Lenox 2001). Further, Florida (1996) argues that firm efforts to improve processes and increase productivity also reduce environmental risks. It is likely that such efforts carry over to other attributes of social performance. Just as capabilities required for lean can leverage green efforts to achieve financial benefits, capabilities required for OP may leverage CSP inputs. Such synergies are likely to be greater at higher levels of OP.

A third resource reflected by OP that can moderate the relationship between CSP and economic performance is slack. Slack is often considered primarily from a financial perspective, but it is described more generally by Bourgeois (1981) as a resource cushion that permits organizations to successfully execute strategy changes or adapt to external challenges. Although greater OP indicates greater efficiencies and, hence, less slack in operational inputs, it can generate slack in other areas such as financial assets and management attention, enabling firms to focus on other strategies, including CSP efforts. As Nohria and Gulati (1996) note, slack in managerial attention is an important consideration, since insufficient slack can result in a short-term performance focus, and an inability to effectively manage less certain initiatives, including CSP. Without sufficient financial resources or management attention, CSP efforts and investments could harm financial performance and increase risk. Greater slack generated by superior OP allows firms to more effectively implement and focus on CSP efforts relative to firms that may not have slack. In contrast, when OP is low, slack is scarce and the economic and risk impacts of CSP are likely not realized by the firm. This suggests a moderating effect of OP on the relationship between CSP and economic performance.

Taken together, these arguments suggest that the effects of CSP on FP and risk are at least partially dependent on the firm's resources associated with OP. At low levels of OP, a firm's lack of management quality, inability to leverage inputs, and insufficient slack limit its abilities to increase economic performance from CSP efforts. But at greater levels of OP, the firm's management quality, capabilities to leverage inputs, and slack resources mean that CSP is more likely to be associated with greater economic performance. Thus, we expect that OP moderates the CSP–FP and CSP–risk relationships. Specifically, for firms with greater OP, the CSP–FP and CSP–risk associations should be more beneficial. Conversely, firms with low OP, even if they excel at CSP, are less able to financially benefit from it.

3. Measures

Our data are obtained from three main sources, Compustat and CRSP for financial data and KLD for CSP data. Waddock (2003, p. 371) notes that the KLD database is among the "best available to scholars given the wide range of companies that KLD evaluates." Rather than using a single source, KLD uses multiple sources to gather data including a "...mixture of company reports, published reports, court decisions and reports, governmental reports, and investigative journalism" (Waddock 2003, p. 372). Chen and Delmas (2011) note that KLD is the predominant source of firm-level CSP measures.

3.1. Dependent Variables

We use four dependent variables to capture the different aspects of FP and risk: (a) profitability as measured by return on assets (ROA); (b) market value as measured by Tobin's q; (c) bankruptcy risk as measured by Altman Z; and (d) stock price volatility (SPV) as measured by the standard deviation of daily stock returns.

ROA: ROA is calculated as the firm's operating income before depreciation, divided by assets.

Tobin's q: Tobin's q is a ratio of the firm's market value to its replacement cost. We measure Tobin's q following Chung and Pruitt (1994); it is calculated as (MV + PS + DEBT)/TA, where: MV is the share price multiplied by the common shares outstanding; PS is the liquidation value of outstanding preferred stock; DEBT is the sum of book value of inventories, long-term debt, and current liabilities less current assets; and TA is the book value of total assets.

Altman Z: Altman Z is a measure of the firm's bankruptcy risk as developed by Altman (1973). It uses multiple, weighted income statement and balance sheet values to measure the financial health of a company, and is commonly used to predict bankruptcy. The weights were estimated empirically by Altman (1973) and are the accepted standard in calculating the bankruptcy risk score. The measure is calculated as: 1.2 × (Working capital/Total assets) + 1.4 × (Retained Earnings/Total assets) + 3.3 × (Earnings before interest and taxes/Total assets) + 0.6 × (Market value/Current Liabilities) + 1.0 × (Sales/Total assets). Greater Altman Z indicates lesser bankruptcy risk.

Stock price volatility (SPV): Stock price volatility is one of the most accepted measures of firm risk (Miller and Bromiley 1990). As in Hendricks and Singhal (2005), we estimate stock price volatility as the standard deviation of daily stock returns over a 1-year period. We label it as SPV.

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3.2. Independent Variables

Flynn and Flynn (2004) note that a common problem with manufacturing capability measures are that the single dimensions often used to represent capabilities do not adequately represent the underlying multi-dimensional constructs. To avoid that issue with our independent variables, we employ a DEA-based approach to accommodate the multiple dimensions of OP and CSP.

Operational productivity (OP): Reflecting the varied inputs that operations managers control to maximize firm outputs, our OP measure captures productivity in labor, inventory, and fixed assets, all of which are classic indicators of productivity for operations. Including multiple inputs is important as firms might elect to strategically concentrate on specific inputs they deem most critical to their particular business context. For example, manufacturers might strive for greater productivity by increasing their fixed assets or inventories to reduce their labor costs, or vice-versa. Rather than establishing predetermined weights for each input, we employ DEA as it calculates an optimal set of weights, permitting firms to achieve the OP efficiency frontier using a variety of paths.

For our DEA-based measure, we use Compustat data items for employees, total inventory, and plant, property, and equipment as inputs, and firm sales as the output. We calculate the DEA scores for the sample firms by industry for each year. We use a VRS, input-oriented DEA model (Banker et al. 1984). The VRS model adds a convexity constraint to the original model of Charnes et al. (1978) to account for non-proportional changes in output relative to input. The dual form of the linear program of the Banker, Charnes, and Cooper (BCC) model is presented as follows:

$$\min \theta$$

$$\text{s.t. } \sum_i x_{ij}\lambda_i \leq \theta x_{jp} \; \forall j$$

$$\sum_i y_{ik}\lambda_i \geq y_{kp} \; \forall k$$

$$\sum_i \lambda_i = 1$$

$$\lambda_i \geq 0 \; \forall i$$

where θ is the efficiency score obtained for decision making unit (DMU) p. In our context, the DMU is the firm-year. The amount of the jth input for the ith DMU is represented as x_{ij}, while the kth output produced by DMU i is expressed as y_{ik}. λ_i s the dual variable that captures the improvements inefficient DMUs can make to become efficient. This is an input-oriented approach that minimizes inputs with respect to the given outputs of a DMU. Efficient DMUs are those that require the least amount of inputs to produce the output and are assigned a score of 1.00. For the OP metric, the most efficient firms are those that maximize sales subject to minimal inventory, fixed assets, and labor.

Corporate social performance (CSP): In order to create the CSP measure, we obtain ratings from the KLD database. KLD rates firms in a variety of areas including community, corporate governance, diversity, employee relations, environment, human rights, product, and controversial businesses such as gambling, firearms, etc. (KLD 2006). For each CSP area, KLD rates various positive and negative items of firm practices and performance using categorical (0/1) variables. A rating of 1 for a positive (negative) item is labeled a "strength" ("concern"); a rating of 0 indicates no particular firm strength (concern) for that item. It is important to note that the positive and negative categories are not necessarily balanced in each CSP area. For example, the environment area as rated by KLD during our sample frame includes five potential strengths and seven potential concerns. Consistent with Chen and Delmas (2011) and earlier literature, our CSP measure excludes ratings for corporate governance and controversial businesses; governance items are typically considered separately from other CSP dimensions, and controversial businesses tend to be time-sensitive and/or firm-specific. See Table 1 for a listing of the KLD rated items used in our analyses.

Another important feature of the KLD data is that firms can have both strengths and concerns related to a specific issue (Griffin and Mahon 1997). As an example, a firm might have an environmental strength in "clean energy" due to its focus on renewable fuels or energy conservation, but also an environmental concern in "climate change" because it still consumes large amounts of carbon-based fuels. Mattingly and Berman (2006) employ exploratory factor analysis to demonstrate that KLD strengths and concerns are not merely opposites but are instead divergent measures representing different constructs. Accordingly, the literature has pursued multiple aggregation approaches for KLD data (see Chen and Delmas (2011) for a description of these approaches). Chen and Delmas (2011) note that the existing aggregation approaches all have inherent weaknesses, and in response, they propose a DEA-based method to calculate the firm's CSP. The DEA approach is beneficial since it is a relative measure of overall efficiency of CSP for any specific firm, and is consistent with our definition of CSP as outlined by Pinney (2001) where positives (i.e., strengths) are maximized and negatives (i.e., concerns) are minimized. As in Chen and Delmas

Table 1 KLD Items Consistently Rated 1999–2009 and Included in Construction of the CSP Measure

CSP Area	Strength item	Concern item	CSP Area	Strength item	Concern item
Employee Relations	Union relations	Union relations	Community	Charitable giving	Investment controversies
	Cash profit sharing	Health & safety		Innovative giving	Negative economic impact
	Employee involvement	Workforce reductions		Support for housing	Tax disputes
	Retirement benefits	Retirement benefits		Support for education	Other
	Health & safety	Other		Non-US charitable giving	
	Other			Other	
Environment	Beneficial products/services	Hazardous waste	Diversity	CEO	Controversies
	Pollution prevention	Regulatory problems		Promotion	Non-representation
	Recycling	Ozone depleting chemicals		Board of Directors	Other
	Clean energy	Substantial emissions		Work/life benefits	
	Other	Agricultural chemicals		Women/minority contracting	
		Climate change		Employment of disabled	
		Other		Gay & lesbian policies Other	
Product	Quality	Product safety	Human Rights	Indigenous peoples relations	Burma
	R&D/innovation	Marketing/contracting		Labor rights	Labor rights
	Benefits to disadvantaged	Antitrust		Other	Indigenous peoples relations
	Other	Other			Other

(2011), we specify the firm-year as the DMU, and we use the strengths as outputs and concerns as inputs to our DEA model.

Given that KLD rates strengths and concerns as 0/1 variables, summations of strengths and concerns are ordinal data. With ordinal measures, a DEA model such as the BCC model proposed by Banker et al. (1984) is not appropriate. Accordingly, Chen and Delmas (2011) use the modification proposed by Cook and Zhu (2006) to account for ordinal data. In order for the DEA method to accommodate ordinal variables, a value is assigned based on the rank position for each output and input. This is accomplished by defining the L-dimensional unit worth vectors, $\gamma_{rk} = (\gamma_{rk}(l)), \text{and} \delta_{ik} = (\delta_{ik}(l))$, where

$$\gamma_{rk}(l) = \begin{cases} 1 & \text{if DMU}\, k \text{ is ranked in the } l\text{th} \\ & \text{position on output } r \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{ik}(l) = \begin{cases} 1 & \text{if DMU}\, k \text{ is ranked in the } l\text{th} \\ & \text{position on input } r \\ 0 & \text{otherwise} \end{cases}$$

The unit worth vectors are subject to a set of linear conditions that requires position l to be higher ranked than position $l + 1$. This leads to the optimization problem:

$$\min \theta - \varepsilon \sum_{r \in R} \sum_{l=1}^{L} \alpha_{rl}^{1} - \varepsilon \sum_{i \in I} \sum_{l=1}^{L} \alpha_{il}^{2} \qquad (1)$$

$$\text{s.t.} \sum_{k=1}^{N} \lambda_k \bar{\gamma}_{rk}(l) - \alpha_{rl}^{1} = \bar{\gamma}_{r0}(l), r \in R_2,\ l = 1, \ldots, L$$

$$\theta \bar{\delta}_{io}(l) - \sum_{k=1}^{N} \lambda_k \bar{\delta}_{ik}(l) - \alpha_{il}^{2} = 0,\ \ i \in I_2,\ \ l = 1, \ldots, L$$

$$\sum_{k=1}^{N} \lambda_k = 1$$

$$\lambda_k, \alpha_{rl}^{1}, \alpha_{il}^{2} \geq 0$$

where: ε s a small value used to bound the multipliers; α_{rl}^{1} and α_{il}^{2} are dual variables for the rank ordered constraints; λ_k is the standard dual variable as in the BCC model; R is the number of ordinal outputs; and I is the number of ordinal inputs. See Cook (2011) for further details.

Input and output weights are assigned based on the optimization procedure, eliminating the need for *a priori*, user-assigned fixed weights; this is an important benefit of the DEA methodology. Similar to the DEA employed for OP, this input-oriented DEA minimizes inputs with respect to the given outputs of a DMU. Efficient DMUs are those with the least inputs and the highest outputs, and are assigned a score of 1.00. The most efficient CSP firms are those that maximize their strengths while minimizing their concerns.

3.3. Control Variables

We control for several other factors that might influence the dependent variables and/or the relationship between the independent and dependent variables.

R&D intensity (*R&D*): R&D intensity is a common control measure for firm performance because R&D can produce more successful products, and higher performing firms tend to spend more on R&D. R&D has also been argued to be an important variable when considering the CSP–FP relationship (McWilliams and Siegel 2001). The variable *R&D* is measured as R&D expenses divided by sales, and all firms that did not report R&D expenses are assumed to have zero R&D intensity.

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Advertising intensity (*AdInt*): Advertising intensity is another common control variable for firm performance and has recently been linked to CSP (Servaes and Tamayo 2013). Advertising intensity is measured as advertising expenses divided by sales, and all firms that did not report advertising expenses are assumed to have zero advertising intensity.

Firm size (*Size*): We control for firm size because larger firms might possess economies of scale and/or scope that enhance or depress the relationships between OP, CSP, FP, and risk. Our proxy for firm size is the log of the firm's total employees lagged one year to reduce collinearity with our measure of OP.

Year: In addition to the above three factors, we also control for year-specific effects using dummy variables.

4. Data Description

Chen and Delmas (2011) apply the DEA methodology described above to generate CSP scores by comparing all firms in one of three broad sectors – manufacturing, finance, or services – in a given year. To permit a finer-grained examination of manufacturing firms within specific industries, we define our DEA comparison groups as all KLD-rated firms in the same four-digit SIC code. We compile a list of manufacturing firms (SIC codes 2000-3999) common across the KLD and Compustat databases to generate our potential sample firms. Our sample is restricted to pre-2010 because KLD, subsequent to its acquisition by RiskMetrics in 2009 and then by MSCI in 2010, changed their ratings system significantly. The more recent KLD ratings evaluate several added categories and place much more emphasis on strengths and less emphasis on concerns. Thus, combining pre- and post-2010 KLD data presents a problem of measurement equivalence.

To compute DEA efficiencies, recommendations for a minimum number of DMUs range from twice the number of inputs and outputs (Golany and Roll 1989), to a more conservative three times the number of inputs and outputs (Bowlin 1998). With the three inputs and one output that we employ for the productivity DEA, a minimum of 12 DMUs are required to ensure that the estimates meet the conservative threshold. For the CSP DEA with six inputs and six outputs, a minimum of 36 DMUs are required to meet the conservative threshold. To consider the greatest number of manufacturing industries and years, we set our selection criterion to those manufacturing industries with at least 16 firms in both Compustat and KLD. To ensure that small industries with low numbers of DMUs are not unduly influencing our results, we later drop the smallest industries as a robustness check.

In 2003, KLD expanded their ratings from approximately 1100 companies per year to include all firms in the Russell 3000 index. Thus, prior to 2003, there are few industry-years with sufficient numbers of firms to permit DEA. In fact, we found no industry-years prior to 1999 that met our minimum DMU criterion. The final sample includes nine different four-digit SIC codes in the manufacturing sector comprising 476 unique firms in the period 1999–2009. We provide description and frequency of the sample in Table 2. As seen in Table 2, the minimum number of industry-year observations that we include in our sample is 16 for SIC 2835 in years 2007 and 2008.

Given that our sample comprises multiple manufacturing industries over a 11-year period; it requires 68 separate industry-year DEA estimations for OP and for CSP. Since DEA results are dimensionless and only meaningful relative to their DMU group, we standardize each OP and CSP measure by industry-year to facilitate comparisons across industries and years. This standardization permits us to distinguish

Table 2 Frequency of Firms in the Nine Manufacturing Industries (four-digit SIC) with the Greatest Number of Firms That Have Both KLD Ratings and Compustat Data 1999–2009

		Years in study												
SIC	Description	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Total	Mean
2834	Pharmaceuticals	18	**15**	26	26	86	101	86	84	86	78	77	683	62.1
3674	Semiconductors	**8**	**14**	35	30	79	82	81	83	76	83	82	653	59.4
2836	Biological products	**3**	**5**	**15**	**8**	57	61	58	57	60	66	71	461	41.9
3845	Electromedical apparatus	**3**	**3**	**4**	**3**	26	30	28	28	31	34	32	222	20.2
3663	Communications equipment	**3**	**3**	**7**	**6**	24	27	23	24	23	23	25	188	17.1
3841	Medical instruments	**5**	**5**	**6**	**5**	19	22	23	22	19	20	23	169	15.4
3842	Orthopedic appliances	**5**	**5**	**4**	**7**	22	24	23	20	19	19	19	167	15.2
3559	Special machinery	**5**	**6**	**8**	**8**	19	21	20	19	19	19	19	163	14.8
2835	Diagnostic substances	**0**	**0**	**4**	**3**	20	24	17	18	16	16	17	135	12.3
	Totals	50	56	109	96	352	392	359	355	349	358	365	2841	258.3

Bolded numbers indicate industry-years with insufficient DMUs (minimum of 16) to permit use of DEA.

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firms that are on the OP or CSP efficiency frontier (i.e., a raw score of 1.00) in an industry that has relatively small differences in efficiency, vs. firms in an industry that might have large differences in OP or CSP within the same year.

As noted, an important advantage of the DEA methodology is that it allows us to consider how firms pursue different approaches to achieve the efficiency frontier. To illustrate how some actual firms in our sample changed their input efficiencies year-to-year, with corresponding changes in their OP and CSP scores, financial performance, and risk, we provide Table 3. For both OP and CSP, we provide examples for firms that increased the efficiency of their inputs but fell into one of four scenarios: (1) did not improve their DEA score; (2) improved their DEA score but did not achieve the efficiency frontier for the industry-year; (3) improved their DEA score and achieved the efficiency frontier for the industry-year; or (4) continued to be on the efficiency frontier for the industry-year. We note that each of the example firms in Table 3 achieved their efficiency improvements via a different method. For OP (see Table 3 Panel A): (1) Balchem improved its Sales per PPE and Employee, yet its OP score did not change compared to the rest of the industry; (2) Genesis Microchip also made improvements in Sales per PPE and Employee, and did improve its OP score; (3) Immucor improved in all three input categories, and achieved the OP frontier; and (4) Dade Behring improved primarily in Sales per Inventory and continued to stay on the OP frontier. For CSP (see Table 3 Panel B): (1) although Asyst Technologies increased its strengths in Diversity and decreased its concerns in Employee Relations and Diversity, its CSP score did not increase; (2) Skyworks Solutions increased its strengths in Products, and increased its CSP score; (3) Idexx Labs increased its strengths in Diversity and Employee Relations to achieve the CSP frontier; and (4) Becton Dickinson increased its strengths in Environment and Products, and decreased its concerns in Employee Relations, to remain on the CSP frontier. These different paths to improvement are consistent with Chen and Delmas (2011), and highlight the benefits of employing a DEA-based approach to generate OP and CSP. The examples in Table 3 also suggest the value of using an overall efficiency score to evaluate performance rather than the individual inputs. As indicated by the

Table 3 Example Firms from the Sample That Improved Performance Year-to-Year in OP Inputs (Panel A) and CSP Inputs (Panel B) with Corresponding Changes in DEA Scores and Dependent Variables

		DEA scores not improved	DEA scores improved but less than frontier	DEA scores improved to frontier	DEA scores remain on frontier
Panel A: Improvements in OP inputs					
ID	Firm	Balchem	Genesis Microchip	Immucor	Dade Behring
	Industry SIC	2834	3674	2835	2835
	Year t	2007	2005	2004	2005
1-year Change in Inputs	Sales/Inventory	7.8%	−1.5%	17.6%	8.2%
	Sales/PPE	37.1%	19.1%	16.4%	1.3%
	Sales/Employees	25.5%	11.6%	22.3%	1.2%
DEA Scores	OP_{t-1}	0.33	0.62	0.86	1.00
	OP_t	0.33	0.76	1.00	1.00
	Change in *OP*	−0.8%	22.6%	16.3%	0.0%
1-year Change in DVs	ROA	−14.6%	188.9%	27.2%	20.0%
	Tobin's q	−13.2%	3.3%	103.3%	39.5%
	Altman Z	−17.8%	25.2%	54.5%	35.3%
	SPV	7.7%	−3.7%	−6.5%	−19.6%
Panel B: Improvements in CSP inputs					
ID	Firm	Asyst Technologies	Skyworks Solutions	Idexx Labs	Becton Dickinson
	Industry SIC	3559	3674	2835	3841
	Year t	2006	2007	2005	2007
1-year change in inputs	Areas with increased Strengths	Diversity	Products	Diversity; Employee Relations	Environment; Products
	Areas with decreased Concerns	Employee Relations; Diversity	n/a	n/a	Employee Relations
DEA scores	CSP_{t-1}	0.73	0.70	0.97	1.00
	CSP_t	0.70	0.85	1.00	1.00
	Change in *CSP*	−4.1%	21.4%	3.1%	0.0%
1-year change in DVs	ROA	−22.9%	46.1%	16.3%	5.0%
	Tobin's q	56.3%	0.8%	35.4%	14.6%
	Altman Z	−32.5%	30.7%	23.9%	5.8%
	SPV	26.0%	−21.8%	−29.3%	−6.9%

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performance of Balchem and Asyst Technologies, even though both firms improved their inputs, their industries improved even more. As a result, their DEA scores decreased, their financial performance was reduced, and their risk profile increased.

Although Chen and Delmas (2011) encourage the use of their DEA-based CSP measure as an independent variable, DEA outputs are typically not employed as independent variables. We therefore proceed cautiously with both our CSP and OP measures by first examining the basic associations between the independent and dependent variables before applying multivariate regression techniques. Table 4 provides descriptive statistics and correlations for our variables. We note a few important points. First, as expected, we find that OP is positively and significantly correlated to the three dependent variables ROA, Tobin's *q*, and Altman *Z*, and negatively and significantly correlated with SPV. However, CSP is only significantly correlated with ROA, Tobin's *q*, and SPV.

To further consider the basic OP–FP and OP–risk relationships, and the CSP–FP and CSP–risk relationships, we plotted the DEA scores against each performance measure. By doing so, we aimed to validate whether the OP and CSP measures behave as predicted by the literature. A few relationships were apparent from the raw data. First, OP has a positive relationship with ROA, Altman *Z*, and Tobin's *q*, and a marginally negative relationship with SPV. The CSP plots indicate a positive relationship with ROA, Tobin's *q*, and Altman *Z*, and a negative relationship with SPV. These plots support the intuition, logic, and literature that increases in OP and CSP are generally associated with increased performance and reduced risk.

Given that Barnett and Salomon (2006, 2012) hypothesize and demonstrate the effect of CSP on FP to be curvilinear, we must consider potential curvilinear effects in our analyses. Using the DEA-based scores for OP and CSP as independent variables presents some estimation challenges. First, since DEA creates numerical scores for each DMU that classify them relative to each other and to the frontier, they cannot be considered as linear measures. Second, DEA scores are not continuous since the raw DEA scores for OP and CSP are constrained (0,1) variables. Third, CSP is discretized in (0,1) as a result of the ordinal DEA methodology developed by Cook and Zhu (2006) and employed by Chen and Delmas (2011). The CSP scores are discretely incremented by the ε value chosen in Equation (1), even though the order of firms is preserved irrespective of ε. Thus, employing non-linear, non-continuous measures to estimate linear effects, and squaring the measures to estimate curvilinear effects is neither appropriate nor interpretable. Accordingly, we categorize the independent variables OP and CSP into three quantiles (i.e., tertiles). We employ tertiles as the most parsimonious means to permit consideration of potential non-linearities. We label the low-score tertiles for OP and CSP as OP1 and CSP1, the medium-score tertiles as OP2 and CSP2, and the high-score tertiles as OP3 and CSP3, respectively. Combining the two categorizations gives us nine (3×3) subgroups of roughly equal size.

Table 5 presents the frequencies of the nine subgroups, and the medians of the standardized OP and CSP scores for each subgroup. Since our OP and CSP scores are standardized by industry-year, the medium (2) category represents firms that are roughly equivalent in OP and/or CSP with their industry peers. The low (1) and high (3) category firms have OP and CSP scores approximately one standard deviation below and above the sample medians, respectively. Table 5 also depicts the median raw data scores for each of the two FP measures and the two risk measures by subgroup. Considering the ROA results in panel d) as an example, we see that ROA is increasing in OP from a median value of 0.086 for the OP1 category to 0.122 for the OP3 category. The relationship between ROA and CSP appears somewhat curvilinear with median values of ROA equal to 0.089 for CSP1, 0.085 for CSP2, and 0.126 for CSP3, respectively. Firms in the subgroup that excel in both OP and CSP (OP3-CSP3) have the greatest median ROA value (0.170). We note similar patterns for Tobin's *q*, Altman *Z*, and SPV.

Table 4 Descriptive Statistics and Correlations for the Dependent, Independent, and Control Variables

		N	Mean	SD	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
ROA	(a)	2086	0.053	0.231	1.000							
Tobin's *q*	(b)	2073	2.359	1.893	—0.066 *	1.000						
Altman *Z*	(c)	2083	11.904	13.029	0.207 *	0.520 *	1.000					
SPV	(d)	2077	3.293	1.550	—0.379 *	—0.053 *	—0.121 *	1.000				
OP	(e)	2086	0.712	0.263	0.093 *	0.183 *	0.138 *	—0.111 *	1.000			
CSP	(J)	2086	0.845	0.130	0.061 *	0.054 *	0.019	—0.052 *	0.286 *	1.000		
R&D	(g)	2086	0.576	3.057	—0.362 *	0.072 *	0.009	0.110 *	0.013	—0.040	1.000	
AdInt	(h)	2086	0.014	0.088	—0.168 *	0.047 *	—0.020	—0.021	0.006	—0.057 *	0.073 *	1.000
Size	(i)	2085	1.045	1.119	0.357 *	—0.124 *	—0.194 *	—0.358 *	0.040	0.168 *	—0.136 *	—0.051 *

Descriptive statistics are not standardized; $^{*}p < 0.05$.

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Table 5 Descriptive Statistics for the Nine Subgroups Formed by Low (1), Medium (2), and High (3) Standardized OP and CSP Scores Including the (a) Number of Observations, and Median Values of (b) Standardized OP, (c) Standardized CSP, (d) ROA, (e) Tobin's *q*, (f) Altman *Z*, and (g) SPV

(a) Number of observations

OP \ CSP	1	2	3
3	221	192	277
2	246	233	216
1	234	291	176

(b) Standardized OP

OP \ CSP	1	2	3
3	0.987	0.989	1.073
2	0.030	0.060	0.171
1	-1.057	-1.141	-1.024

(c) Standardized CSP

OP \ CSP	1	2	3
3	-0.888	-0.080	1.244
2	-0.887	-0.151	1.084
1	-0.787	-0.176	0.905

(d) ROA

OP \ CSP	1	2	3	Median
Median	0.089	0.085	0.126	
3	0.094	0.078	0.170	0.122
2	0.085	0.085	0.110	0.091
1	0.090	0.091	0.065	0.086

(e) Tobin's *q*

OP \ CSP	1	2	3	Median
Median	1.760	1.758	2.053	
3	1.818	2.315	2.346	2.141
2	1.814	1.749	2.052	1.881
1	1.628	1.545	1.678	1.593

(f) Altman *Z*

OP \ CSP	1	2	3	Median
Median	8.538	8.956	9.239	
3	9.507	10.969	10.383	10.340
2	8.308	8.604	8.905	8.654
1	7.522	8.023	8.069	7.955

Note : Increased Altman *Z* indicates reduced risk.

(g) SPV

OP \ CSP	1	2	3	Median
Median	3.146	3.178	2.775	
3	3.256	3.376	2.579	3.017
2	3.178	3.017	2.569	2.898
1	3.071	3.114	3.122	3.098

Note : Reduced SPV indicates reduced risk.

5. Estimation and Results

To examine the relationships of OP and CSP to FP and risk, we pursue a panel data approach to estimate the model. Given the possibility of time-invariant, firm-specific, unobservable factors such as management capabilities, we estimate firm-level fixed effects regression models. In addition, we include time dummies to account for any exogenous year-specific events that may influence firm results. We estimate three models: Model 1 contains only control variables; Model 2 adds the main effects of OP and CSP; and Model 3 adds the interaction effects between OP and CSP. For both OP and CSP, the low category (1) is excluded in the regressions to serve as the referent category.

We note that the fixed effects approach is conservative given that our data has 476 firms. Thus, we also employ a random effects approach as an added check. Since our data has multiple industries, Bell and Jones (2015) recommend explicitly modeling these higher order variances to account for heterogeneity at the industry-level in addition to the firm-level. Accordingly, we employ random intercepts at both the industry- and firm-levels. This also allows us to model both within- and between-group variance components. Although the random effects model is more efficient given the lesser number of parameters to estimate, it does not account for time-invariant, unobserved variables at the firm-level. Accordingly, we present the random effects results as robustness checks.[1] These results are presented as Model 4. All models are estimated with cluster-robust standard errors.

5.1. OP Moderation of the CSP–FP and CSP–Risk Relationships

We now present the regression results for each of the four dependent variables.

Profitability (ROA): Table 6 presents the results of the regressions with ROA as the dependent variable.

Table 6 Regression Model Results for Profitability (as measured by ROA) Demonstrating Main Effects and Interactions of OP and CSP

	Model 1 -controls only	Model 2 -controls and main effects	Model 3 -controls, main effects, and interaction	Model 4 -random effects
Constant	0.120***	0.116***	0.112***	0.031
	(0.017)	(0.014)	(0.011)	(0.027)
Size	0.018	0.025	0.026	0.054***
	(0.024)	(0.021)	(0.020)	(0.014)
R&D	−0.012***	−0.012***	−0.012***	−0.014***
	(0.003)	(0.003)	(0.003)	(0.002)
AdInt	−1.093***	−1.085***	−1.090***	−0.477***
	(0.231)	(0.234)	(0.225)	(0.058)
OP2		0.034***	0.025**	0.021***
		(0.008)	(0.009)	(0.006)
OP3		0.074***	0.063***	0.057***
		(0.013)	(0.008)	(0.008)
CSP2		0.004	−0.012*	−0.012†
		(0.004)	0.006	(0.006)
CSP3		−0.003	−0.002	−0.005
		(0.006)	(0.012)	0.012
OP2·CSP2			0.024*	0.024*
			(0.011)	(0.012)
OP2·CSP3			0.001	0.005
			(0.015)	(0.014)
OP3·CSP2			0.032*	0.028†
			(0.015)	(0.016)
OP3·CSP3			−0.001	0.006
			(0.016)	(0.018)
Firm effects	Y	Y	Y	N
Year effects	Y	Y	Y	Y
N	2085	2085	2085	2085
AIC	−4354.2	−4422.6	−4430.0	−2381.4
Log-Likelihood	2185.1	2219.3	2223.0	1198.7

Standard errors in parentheses below the coefficient estimates. OP is Operational Productivity; CSP is Corporate Social Performance. Size is ln (employees) in year $t-1$. Referant categories are OP1 and CSP1. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

The main effects of OP and CSP can be inferred from the significance of the subgroups for increasing levels of each variable. Model 2 results indicate that OP has a significant positive association with ROA ($\beta_{OP2} = 0.034$, $p < 0.001$; $\beta_{OP3} = 0.074$, $p < 0.001$) but CSP does not have a significant relationship to ROA.

We now discuss the impact of the interaction between OP and CSP. Model 3 results indicate that OP is still positively associated with ROA ($\beta_{OP2} = 0.025$, $p < 0.01$; $\beta_{OP3} = 0.063$, $p < 0.001$) albeit the magnitude is slightly less than in Model 2. CSP has a marginally negative relationship with ROA ($\beta_{CSP2} = -0.012$, $p < 0.05$; $\beta_{CSP3} = -0.002$, $p > 0.10$). A significant OP·CSP interaction in Model 3 indicates a moderation effect of OP on the CSP–ROA relationship. The interaction coefficients that are significant are those for the categories OP2·CSP2 ($\beta_{OP2CSP2} = 0.024$, $p < 0.05$) and OP3·CSP2 ($\beta_{OP3CSP2} = 0.032$, $p < 0.05$). Thus, the evidence suggests that the main effect of OP is strong and positive for ROA, and that OP is a significant moderator of the CSP–ROA relationship. Table 6 also presents Model 4 results, demonstrating that a random effects approach yields substantively similar results.

Market value (Tobin's q): Table 7 presents the results of the regressions for Tobin's q. As with ROA, the Model 2 results demonstrate a positive relationship between OP and Tobin's q. Higher productivity is associated with higher Tobin's q. Unlike ROA, the results also indicate a significant, positive relationship between CSP and Tobin's q ($\beta_{CSP2} = 0.204$, $p < 0.05$; $\beta_{CSP3} = 0.105$, $p > 0.10$).

However, adding the interaction effects in Model 3 reduces the magnitude and significance of the OP and CSP main effects. Although none of the OP·CSP categories is significant, the reduction in OP and CSP main effects suggests some moderation effect in the CSP-Tobin's q relationship. The results of the random effects analysis (Model 4) in Table 7 are substantively similar.

Bankruptcy risk (Altman Z): Table 8 presents the results of the regressions for Altman Z. We remind the reader than an increase in Altman Z is a *reduction* in bankruptcy risk. Accordingly, we expect the directionality of the OP and CSP main effects and interactions on Altman Z to be consistent with those for ROA and Tobin's q. Model 2 results show a strong and positive association between OP and Altman Z, and a significant positive association between CSP and Altman Z.

Model 3 reveals that the main effects of OP and CSP on Altman Z are eliminated, and the OP·CSP

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Table 7 Regression Model Results for Market Value (as measured by Tobin's *q)* Demonstrating Main Effects and Interactions of OP and CSP

	Model 1 -controls only	Model 2 -controls and main effects	Model 3 -controls, main effects, and interaction	Model 4 -random effects
Constant	2.753***	2.683***	2.683***	3.772***
	(0.154)	(0.146)	(0.138)	(0.235)
Size	−0.450*	−0.396*	−0.393*	−0.262***
	(0.204)	(0.192)	(0.189)	(0.045)
R&D	−0.019†	−0.019†	−0.019†	−0.010*
	(0.010)	(0.011)	(0.011)	(0.004)
AdInt	−0.195	−0.176	−0.161	0.059
	(3.864)	(3.538)	(3.519)	(0.489)
OP 2		0.299***	0.258†	0.372**
		(0.079)	(0.132)	(0.144)
OP 3		0.375†	0.360	0.436*
		(0.200)	(0.225)	(0.172)
CSP 2		0.204*	0.177*	0.151†
		(0.089)	(0.088)	(0.075)
CSP 3		0.105	0.072	0.118
		(0.082)	(0.106)	(0.133)
OP 2·CSP 2			0.024	−0.030
			(0.137)	(0.127)
OP 2·CSP 3			0.118	0.004
			(0.211)	(0.218)
OP 3·CSP 2			0.077	0.196
			(0.187)	(0.155)
OP 3·CSP 3			−0.013	0.022
			(0.242)	(0.183)
Firm effects	Y	Y	Y	N
Year effects	Y	Y	Y	Y
N	2072	2072	2072	2069
AIC	6064.8	6043.4	6042.1	7469.0
Log-Likelihood	−3024.4	−3013.7	−3013.0	−3726.5

Standard errors in parentheses below the coefficient estimates. OP is Operational Productivity; CSP is Corporate Social Performance. Size is ln (employees) in year *t*–1. Referant categories are OP1 and CSP1. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

interaction effect is positive and significant ($\beta_{OP3CSP2} = 2.769$, $p < 0.10$; $\beta_{OP3CSP3} = 2.902$, $p < 0.01$. The evidence suggests that OP significantly moderates the CSP–Altman Z relationship. Again, modeling random effects (see Model 4 in Table 8) yields substantively similar results.

Stock price volatility (SPV): Table 9 presents the results of the regressions for SPV. We note that, unlike Altman Z, an increase in SPV represents an *increase* in risk rather than a reduction. Thus, we expect the directionality of the OP and CSP main effects and interactions on SPV to be opposite those for ROA, Tobin's *q*, and Altman Z. The Model 2 results for OP are insignificant but, unexpectedly, CSP appears to increase SPV ($\beta_{CSP3} = 0.121$, $p < 0.01$).

We see little change in the Model 3 results relative to the Model 2 results; the main effect of OP remains insignificant, and the main effect of CSP remains significantly positive ($\beta_{CSP3} = 0.123$, $p < 0.01$). None of the OP·CSP interaction categories are significant. The empirical evidence suggests that the main effect of CSP is slightly positive for SPV, and that OP is not a significant moderator of the CSP–SPV relationship. The results from the random effects analysis (see Model 4 in Table 9) indicate marginal, negative significance for the interaction effect.

Marginal plots: To provide a visual interpretation of the moderation results, Figure 1 depicts the predicted margins plots. As shown in Table 5a, there are approximately 200 observations in each of the nine OP·CSP subgroups. We use the estimated regression coefficients from Model 3 in Tables 6–9 to predict the values for each observation, and then compute the average for each of the nine subgroups to generate the plots in Figure 1. In all four Figure 1 plots, we see that CSP has little impact when OP is low (OP1); that is, the OP1 plots are essentially flat. We also see in Figures 1a and b that FP is generally increasing in OP (i.e., FP at OP3 > FP at OP2 > FP at OP1) and, in Figures 1c and d, risk is generally reducing in OP (i.e., risk at OP3 < risk at OP2 < risk at OP1), reflecting the beneficial relationship we find between OP, FP, and risk in our analyses. In Figure 1a, the moderating effect of OP on the CSP–ROA relationship is apparent. Increases in CSP from low (CSP1) to medium (CSP2) have marginally negative impacts on ROA regardless of OP. But increases in CSP from medium (CSP2) to high (CSP3) result in increases in ROA that are increasing in OP. In Figure 1b, we see the strong effect of OP on the CSP–Tobin's *q* relationship but we also note the nonuniform effects of OP. The higher levels of OP (OP2

Table 8 Regression Model Results for Bankruptcy Risk (as measured by Altman *Z*) Demonstrating Main Effects and Interactions of OP and CSP

	Model 1 -controls only	Model 2 -controls and main effects	Model 3 -controls, main effects, and interaction	Model 4 - random effects
Constant	12.920***	12.520***	12.733***	15.856***
	(1.186)	(1.137)	(1.122)	(1.333)
Size	−5.544***	−5.294***	−5.306***	−3.328***
	(1.243)	(1.232)	(1.193)	(0.750)
R&D	−0.189*	−0.181*	−0.180*	−0.151***
	(0.079)	(0.085)	(0.082)	(0.030)
AdInt	−19.700	−19.560	−17.871	−7.521*
	(22.120)	(20.260)	(20.080)	(3.563)
OP2		1.717***	1.369	1.910*
		(0.469)	(0.914)	(0.964)
OP3		2.620**	0.752	1.757
		(0.818)	(1.121)	(1.148)
CSP2		0.978*	0.122	0.326
		(0.417)	(0.672)	(0.650)
CSP3		0.996*	−0.070	0.167
		(0.453)	(0.848)	(1.133)
OP2·CSP2			0.363	0.297
			(1.279)	(1.164)
OP2·CSP3			0.745	1.318
			(0.832)	(0.931)
OP3·CSP2			2.769†	2.366*
			(1.442)	(1.069)
OP3·CSP3			2.902**	3.657**
			(1.077)	(1.257)
Firm effects	Y	Y	Y	N
Year effects	Y	Y	Y	Y
N	2082	2082	2082	2084
AIC	13333.5	13309.3	13299	15316.2
Log-Likelihood	−6658.7	−6646.6	−6641.5	−7650.1

Increased Altman *Z* indicates reduced risk. Standard errors in parentheses below the coefficient estimates. OP is Operational Productivity; CSP is Corporate Social Performance. Size is ln(employees) in year $t-1$. Referant categories are OP1 and CSP1. $^{\dagger}p < 0.10$, $^{*}p<0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

and OP3) and CSP (CSP2 and CSP3) are associated with significantly greater Tobin's q. An interesting observation is that the highest performing subgroup is the group high in OP (OP3) but only moderate in CSP (CSP2). We have no obvious explanation for this result other than the potentially curvilinear effect of CSP on Tobin's q as theorized by Barnett and Salomon (2006, 2012). Predicted margins of Altman Z are presented in Figure 1c; we observe a pattern similar to that seen for ROA. Figure 1d illustrates the predicted margins of SPV; we note the pattern is inverted due to the positive relationship of SPV to risk.

In summary, our interaction analyses provide support for the moderation effect of OP on the CSP–FP and CSP–risk relationships when we consider the accounting-based measures of ROA and Altman Z. At moderate and high levels of OP, FP is generally increasing in CSP, and risk is generally decreasing in CSP. But at low levels of OP, CSP shows no significant relationship with ROA or Altman Z. Although the directionality of the results for the market-based measures of Tobin's q and SPV are consistent for the moderation effect of OP and the CSP–FP and CSP–risk relationships, they are statistically insignificant.

5.2 Excellence in Both OP and CSP

We now consider whether firms that excel in both OP and CSP enjoy better financial performance and less risk than firms that excel only in OP or only in CSP.

To test whether firms that excel (third tertile) in both OP and CSP experience greater FP and less risk than firms excelling in only one dimension, and not the other, we use the estimated regression coefficients from Model 3 in Tables 6–9 to compute the predicted margins for the subgroups of interest. For each of the FP and risk measures, the differences in predicted margins are calculated between firms that excelled in both OP and CSP and firms that excelled in only CSP or OP. The significance levels are calculated using a t-distribution, and are Bonferroni-adjusted to account for the multiple comparisons. Table 10 presents the results of our pairwise comparisons. As a reminder, reduction in risk is indicated by an increase in Altman Z but a decrease in SPV. For all four dependent variables—ROA, Tobin's q, Altman Z, and SPV—the

Table 9 Regression Model Results for Stock Price Volatility (as measured by SPV) Demonstrating Main Effects and Interactions of OP and CSP

	Model 1 -controls only	Model 2 -controls and main effects	Model 3 -controls, main effects, and interaction	Model 4–random effects
Constant	4.392***	4.383***	4.393***	4.604***
	(0.229)	(0.220)	(0.224)	(0.188)
Size	−0.146*	−0.161**	−0.163**	−0.549***
	(0.060)	(0.056)	(0.058)	(0.057)
R&D	0.031***	0.032***	0.031***	0.034***
	(0.009)	(0.009)	(0.009)	(0.010)
AdInt	−1.077	−1.095	−1.100	−0.564**
	(0.969)	(0.966)	(0.894)	(0.178)
OP2		0.006	0.022	0.074
		(0.056)	(0.068)	(0.072)
OP3		−0.103	−0.056	−0.048
		(0.155)	(0.143)	(0.077)
CSP2		0.023	0.071	0.047
		(0.042)	(0.045)	(0.057)
CSP3		0.121**	0.123**	0.124*
		(0.041)	(0.046)	(0.049)
OP2·CSP2			−0.064	−0.157*
			(0.087)	(0.077)
OP2·CSP3			0.022	−0.109
			(0.099)	(0.130)
OP3·CSP2			−0.104	−0.099
			(0.082)	(0.073)
OP3·CSP3			−0.036	−0.088
			(0.077)	(0.086)
Firm effects	Y	Y	Y	N
Year effects	Y	Y	Y	Y
N	2079	2079	2079	2076
AIC	4473.5	4466.3	4465.3	6194.5
Log-Likelihood	−2228.8	−2225.2	−2224.6	−3089.3

Reduced SPV indicates reduced risk. Standard errors in parentheses below the coefficient estimates. OP is Operational Productivity; CSP is Corporate Social Performance. Size is ln(employees) in year $t-1$. Referant categories are OP1 and CSP1. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

performance of the OP3-CSP3 subgroup is significantly more beneficial ($p < 0.001$) than both the OP3-CSP1 and OP1-CSP3 subgroups. Thus, the evidence suggests that for both financial performance and risk, firms excelling in both OP and CSP outperform firms that excel only in one dimension.

5.3. Robustness Checks

We perform several checks to assess the robustness of our results. First, as discussed in section 4, DEA estimations require the minimum number of DMUs to be two or three times greater than the number of DEA inputs and outputs. To assess the sensitivity of our results to this requirement, we drop the industry with the smallest number of DMUs (SIC 2835) from our analyses. Using only the DEA estimates of OP and CSP for the remaining eight industries, the results for all four dependent variables are substantively similar. We repeat this procedure dropping the two smallest industries (SIC 2835 and SIC 3559), and the three smallest industries (SIC 2835, SIC 3559, and SIC 3842). Again, the results for all four dependent variables are substantively similar suggesting that sufficient DMUs to obtain our DEA estimates is not a major concern.

Next, we assess the sensitivity of our results to the firm size control. We use ln(total assets$_{t-1}$) rather than ln(employees$_{t-1}$), and again find similar results. Last, we check for the influence of control variables. We estimate Model 3 without the control variables to assess their influence. Our results are again substantively the same.

As explained in section 4, our data are restricted to pre-2010 due to substantive changes in ratings that KLD undertook beginning in 2010. To investigate the impact of the KLD measurement changes, we perform DEAs for each of our nine sample industries for each year 2010–2013. As expected given the changes in input and output measures, the resulting DEA scores for CSP exhibit a substantially different distribution than those from the pre-2010 data. This confirms our concerns with measurement equivalence. Determining the efficacy of changes in KLD measures that occurred in 2010 deserves further research and scrutiny but it is not our aim in this study. Instead, we use the more well-known and well-understood KLD ratings pre-2010 to examine our research questions.

As discussed above in section 5.1 and shown in the Model 4 results of Tables 6–9, we employed random effects analysis rather than fixed effects to improve

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Figure 1 Marginal Means for the Nine Subgroups Formed by Low (1), Medium (2), and High (3) OP and CSP Scores, as Predicted by the Model 3 Regressions; Panel a) Presents ROA; Panel b) Presents Tobin's *q*; Panel c) Presents Altman *Z*; Panel d) Presents SPV

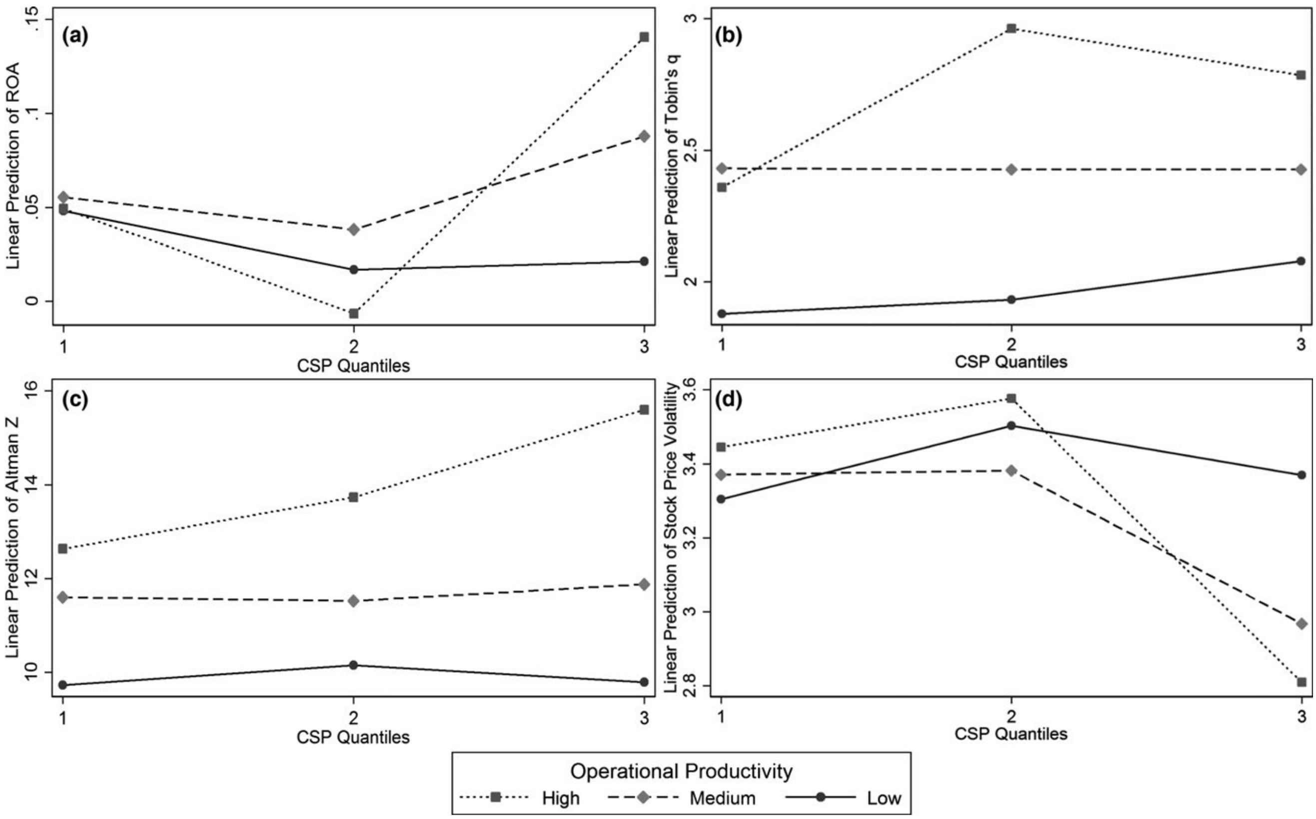

Table 10 Pairwise Comparison Contrasts Between the Subgroup of Firms That Excel in Both OP and CSP (OP3-CSP3) and the Subgroups of Firms that Excel Only in OP (OP3-CSP1) or Only in CSP (OP1-CSP3)

	OP3-CSP3 vs. OP3-CSP1	OP3-CSP3 vs. OP1-CSP3
ROA	0.091***	0.119***
	(0.003)	(0.007)
Tobin's *q*	0.426***	0.708***
	(0.078)	(0.095)
Altman *Z*	2.969***	5.817***
	(0.294)	(0.442)
SPV	−0.637***	−0.561***
	(0.021)	(0.060)

Increased Altman *Z* indicates reduced risk. Reduced SPV indicates reduced risk. Standard errors in parentheses below the contrasts. OP is Operational Productivity; CSP is Corporate Social Performance. Statistical significances are Bonferroni-corrected; ***$p < 0.001$.

the efficiency of our estimation process (note that we have 476 firms). The results from the random effects models are essentially unchanged for the two accounting-based measures (ROA and Altman *Z*) but marginally strengthened for the two market-based measures (Tobin's *q* and SPV). This suggests that firm-level omitted variables are not a major concern, at least for our accounting-based measures of financial performance and risk. However, the stronger results from random effects for our two market-based measures (Tobin's *q* and SPV) deserve consideration. There are at least two explanations. First, given the greater volatility in market-based measures, and the lesser overall significance of our results for Tobin's *q* and SPV, it seems reasonable that the increased power and efficiency of random effects estimates (especially given our data structure of large *N*, small *T*) has a greater impact on the significance of those results. In other words, the relatively low signal-to-noise ratios of the market-based measures might require the increased efficiency from random effects to detect the signals. Alternatively, the firm-level fixed effects might indeed be controlling for significant, time-invariant, omitted variables such as management skill and/or other organizational capabilities.

6. Discussion and Conclusions

Based upon our findings, we discuss a number of implications for researchers and practitioners. First, we consider the main effects of OP on FP and risk. Our finding that firm-level productivity (as measured by OP) is positively and significantly associated with financial performance and bankruptcy risk is largely consistent in our analyses. This finding supports the strongly held assumption that productivity in manufacturing firms is critical to their financial and risk performance. The relationship is especially strong for current profitability (as measured by ROA) but less so for bankruptcy risk (as measured by Altman *Z*) and market value (as measured by Tobin's *q*). We find no significant relationship between OP and stock price volatility (as measured by SPV). This suggests that while greater productivity translates into improved bottom line results, its potential to directly reduce stock price volatility, might not be as great. Considering that the efficiency focus typical of productive manufacturing firms is exploitative and leverages tangible resources rather than the intangibles, the results in our sample appear consistent with intuition.

In contrast, our analyses reveal that the main effect of CSP is most significant for Tobin's *q* and SPV. CSP has a significant, positive effect on Tobin's *q* (see Table 7). Given that Tobin's *q* represents intangible value of the firm rather than current profitability, our results suggest that performance impacts of CSP are likely forward-looking. Specifically, greater CSP can improve reputation, attract superior employees, and give the firm greater market presence. Further, greater CSP might help the firm to garner more consumer attention through positive media (Byun and Oh 2014). Clearly, these aspects might result in future payoff and contribute to superior intangible value of the firm. Surprisingly, CSP appears to actually increase stock price volatility (see Table 9). We have no ready explanation for the unexpected positive relationship between CSP and SPV. As discussed in section 2.2, the bulk of theory and evidence predicts a negative relationship between CSP and risk. We can only conjecture that CSP might potentially increase stock price volatility because of costly CSP initiatives that may not be effective in satisfying stakeholders. Alternatively, as Weber (2008) suggests, the increased profile of good-CSP firms might prompt targeting by NGOs and other activists. We also note that, although our finding of an insignificant CSP impact on ROA and Altman *Z* might be disappointing to some, it appears that firms do not experience significant negative effects to their profits or bankruptcy risk despite the increased investments that CSP might require.

Next, Model 3 results for the accounting-based dependent variables show that the OP·CSP interaction effects dominate the main effects of CSP. Specifically, the results indicate a positive interaction effect between OP and CSP for both ROA and Altman *Z*, and marginally so for Tobin's *q*. Thus, we conclude that the direct relationship between CSP, FP, and risk is not strong but instead largely contingent on other factors, a finding consistent with prior research that has primarily examined strategic and marketing dimensions (e.g., McWilliams and Siegel 2001, Sen et al. 2006). None of the past studies in CSP that examine the impact of contingent factors examine firm-level productivity as a key variable. Further, our interaction results indicate an OP threshold value required for superior FP and risk, below which CSP yields no performance benefits, but beyond which CSP increases performance. OP does not appear to have a significant moderating effect on the CSP–SPV relationship. A key contribution of our interaction results to the literature is recognizing the fundamental role of operations in leveraging CSP for economic benefit. This aspect has not been recognized in either the operations or CSP literature streams.

Most operations managers will likely agree that improving OP is their "main" job, but many of those same managers might not realize the importance of how OP facilitates the superior CSP–FP and CSP-risk links. Our findings place operations management as a key aspect of the CSP–FP and CSP-risk discussion. Although the relationships we demonstrate between OP, CSP, financial performance, and risk are important and easily understood, the implications to managers might not be as obvious given that our operationalizations of OP and CSP are DEA-based measures, not management decision variables. However, the examples we provide in Table 3 are suggestive for management action. Not only should managers concern themselves with greater efficiencies in operational inputs or the various strengths and concerns as measured by KLD, but they need to be cognizant of how these variables relate to the rest of their industry peers. As illustrated in Table 3, firm-level efficiency improvement is necessary but not sufficient to impact financial performance and risk. Instead, firm-level improvement relative to industry peers is critical. Further, the examples in Table 3 suggest that managers have multiple pathways to become industry-leading by focusing on different aspects of social responsibility and/or operations. It does not appear that concentrating on any single dimension of OP or CSP is inherently advantageous but rather managing trade-offs to achieve or maintain the efficient frontier is the key. Thus, managers have flexibility in how they approach CSP and OP in their quest to maximize financial performance and minimize risk.

The most important managerial implication of our research is that pursuing CSP at the expense of OP does not seem to be a fruitful path. Firms in our sample with high CSP but low OP did not fare well in regards to ROA, Tobin's *q*, Altman *Z*, or SPV (see Figure 1). Instead, managers must achieve a threshold level of OP, at least on par with industry peers, before improvements in CSP are associated with increased financial performance and reduced risk.

Our finding of an interaction effect between OP and CSP suggest similarities to the cumulative capabilities model described by Ferdows and De Mepyer (1990). In describing the relationship between quality and cost, Ferdows and De Mepyer (1990) argue that if a firm has quality as a foundational, lasting manufacturing capability, it is generally able to also improve its cost performance without sacrificing quality. However, if quality is not a foundational capability, cost cuts are likely achieved via the trade-off model and so are accompanied by quality problems. In our context, the empirical evidence suggests that OP might be a foundational, lasting manufacturing capability similar to quality upon which other capabilities (such as CSP) can be built. The exact nature of the direct relationship between OP and CSP is under-explored and can be the subject of fruitful research.

Focusing on the dependent variables, it is important to note that several past studies examined a single dimension of economic performance. For example: Barnett and Salomon (2012) considered CSP impacts on profitability, as proxied by ROA and net income; and Bouslah et al. (2013) examined CSP impacts on risks, as proxied by stock price volatility. By considering two measures for FP and two measures for risk, we provide a more complete picture of CSP impacts to economic performance. Our results illustrate that: OP is most important for profitability and bankruptcy risk; CSP is most associated with market value and stock price volatility; and the OP·CSP interaction is important for both FP and risk. Further, given that bankruptcy risk is a primary measure of economic survival for firms, the significant relationship we demonstrate between OP·CSP and bankruptcy risk provides evidence of the linkage between environmental, social, and economic sustainability, the oft-discussed triple bottom line. Recent anecdotal work has focused on examining the impact of CSP on firms' longevity (Sahut et al. 2011). Our study adds to this early debate by finding empirical evidence of the joint role of CSP and OP on reducing bankruptcy risk, and hence, increasing a firm's longevity.

6.1. Limitations and Conclusions

Our work is not without its limitations. Given that our focus is on OP (with inventory, fixed assets, and labor as inputs), it drives us to consider only manufacturing firms, we can make no inferences regarding firms engaged primarily in service industries. Consideration of service firms likely requires a different operationalization of OP (e.g., perhaps without inventories) and is grounds for future research. Further, our DEA-based approach requires relatively large comparison group sizes to yield a sufficient number of DMUs, and so CSP data availability restricts our manufacturing sample to only nine specific industries. Although the nine industries we consider are large and economically significant, they might not be representative of all manufacturing sectors. Our KLD data is also restricted to the 11-year period 1999–2009. Consideration of other time periods will require alternative CSP data sources.

Further, in our analyses, we discern the direction, magnitude, and significance of the associations between OP, CSP, FP, and risk. This is sufficient to address our research question of whether OP interacts with CSP to provide superior performance, but it does not directly address the much-studied but still-debated CSP–FP and CSP-risk causality questions. As Orlitzky et al. (2003) note, "good management" theory predicts that CSP leads to good FP and reduced risk by better satisfying various stakeholder groups, whereas "slack resources" theory posits that good FP generates means which can then be spent on CSP. In their meta-analysis, Orlitzky et al. (2003) find empirical evidence for both theories, suggesting a mutually reinforcing "virtuous cycle" between CSP and FP, and CSP and risk. Considering our research context and variable operationalizations, the stakeholder groups potentially addressed by CSP include communities, society, employees, and consumers, among others. Further, high levels of OP should generate slack resources since employees, inventories, and fixed assets are minimized relative to sales. Thus, both theories highlighted by Orlitzky et al. (2003) certainly apply. Although our empirical techniques do not prove causality, the multiple robustness checks we describe in Section 5.3 reduce endogeneity concerns. By using longitudinal data and accounting for firm-level effects in our analyses, we reduce the concern of potential time-invariant omitted variables but we cannot rule out the possibility that some other time-variant variables may impact the relationships between OP, CSP, FP, and risk.

In summary, our research yields important findings. We confirm the criticality of OP to the financial performance and financial risk of the firm. We also find that CSP alone is not strongly influential on firm financial performance or risk when controlling for OP. Value is derived from CSP only under moderate and high levels of OP. Our joint examination of OP and CSP demonstrates that the best-performing firms excel on both dimensions, not just one. Firms that focus solely on operational productivity perform well, but do not achieve the financial performance enabled by also developing their corporate social performance.

Note

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